CORN KERNEL BREAKAGE CLASSIFICATION BY MACHINE VISION USING A NEURAL NETWORK CLASSIFIER

K. Liao, M. R. Paulsen, J. F. Reid, B. C. Ni, E. P. Bonifacio-Maghirang
STUDENT MEMBER ASAE MEMBER ASAE MEMBER ASAE

ABSTRACT. *A machine vision system was developed to identify corn kernel breakage based on kernel shape profile for automated corn quality inspection. The profile of a corn kernel was sampled into a sequence of one-dimensional digital signals based on its binary image. Shape parameters were selected by analyzing the kernel profile and were sent into a machine learning algorithm to train for a shape membership function of broken versus whole kernel. This system provided successful classifications of 99% for 720 whole kernels and 96% for 720 broken flat kernels, and of 91% for 720 whole kernels and 95% for 720 broken round kernels, respectively.* **Keywords.** *Machine vision, Corn breakage, Neural networks.*

The profile shape of corn kernels is very important for quality inspection involving the detection of broken kernel or whole kernel status. Presently, the determination of whole kernel percentages is rarely performed because it involves considerable training and is a tedious human inspection process. The inspection of corn for percentages of whole kernels is a very time-consuming process even on relatively small 50-g samples. Such tests will not become feasible for large-scale inspection and grading unless the inspection process can be automated. For a feasible, automatic, corn quality inspection system, high-speed real-time classification of the profile shapes of corn kernels is a fundamental requirement.

Machine vision is useful for extracting profile shape features of the grain kernel for variety classification and quality inspection. Zayas et al. (1985, 1986, 1989) used a machine vision system to extract morphological profile shape features from wheat images and used these features to discriminate wheat varieties and nonwheat components. They used kernel dimensions of length, width, and other shape factors such as aspect ratio and convex perimeter as a kernel dimension-based profile shape descriptor. Lai et al. (1986) used similar techniques to extract morphological profile shape features from cereal grain kernels and to identify cereal seed types by their profile pattern. Sapirstein et al. (1987) and Neuman et al. (1987) classified cereal grains using the morphological profile shape features of the grain which were extracted from digitized binary images of grain. Features such as kernel geometric dimensions and Fourier spectrum profile descriptors were used as classification criteria. Ding et al. (1990) used a set of profile symmetry factors along the principle axis of corn kernels to classify the corn kernel breakage along the edge area. It was reported that the profile symmetry method correctly classified approximately 88% of both whole and broken kernels. Zayas et al. (1990) used a set of morphological parameters to discriminate whole corn kernels from broken corn kernels. Statistical discriminant functions from SAS procedures were used to perform shape discriminant analysis. The results indicated that the corn kernel morphological parameters could accurately discriminate whole kernels from broken kernels. However, all these techniques were possible only for applications with little or no time constraints.

A kernel profile shape classifier uses a relationship between profile shape features and shape categories of a kernel in order to learn a profile shape membership function. The relationship between shape features and shape categories is complex and cannot be described with simple parameters or discriminant functions. The input features are continuous real number attributes and contain high-level background noise which is generated and accumulated during data collecting and processing procedures. Complex relationships are difficult to learn using traditional statistical methods or rule-based knowledge systems (Buchanan and Shortliffe, 1984).

A neural network classifier was used to learn the relationships between kernel shape features and kernel shape categories. Neural networks are capable of learning concepts that are not linearly separable and concepts dealing with uncertainty, noise, and random situations. Neural networks have been used to model and classify the shape differences of agricultural products. Brandon et al. (1990) used a counterpropagation paradigm to build a neural network classifier for carrot tip shape classification into five categories. The classifier was found to have an average misclassification rate of 11.5%. Paulsen et al. (1992) used the backpropagation algorithm to model the

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The authors are **Ke Liao**, Post Doctoral Researcher, **Marvin R. Paulsen**, Professor, **John F. Reid**, Associate Professor, **Bingcheng Ni**, Ph.D. Graduate Research Assistant, and **Elizabeth P. Bonifacio-Maghirang**, Research Assistant, Agricultural Engineering Dept., University of Illinois, Urbana.

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shape differences between the whole and broken corn kernels by using Fourier coefficients of the kernel profile for the crown end and sides of a kernel as shape features. Their neural network corn kernel whole/broken classifier was built from the neural network model and had a successful classification rate of 95% for both whole and broken kernels.

Objective

The objective of this research was to develop a neural network-based corn kernel profile shape discrimination system which could accurately classify different kernel shapes for on-line classification of broken kernels and whole kernels.

Materials and Methods

Image Acquisition

Image System. A Matrox Electronic System Ltd. model Image-1280 real-time image processing board and an Image-RTP real-time processor (Quebec, Canada) were used to collect images obtained from a SONY Model XC-711 CCD RGB 768(H) × 493(V) color camera which included a C-mount adapter to support a Micro-Nikkor f/2.8 55 mm lens. The image processing board included a TMS34020 local central processing unit (CPU), a color digitizer with a resolution of 1024 × 1024 pixels with 8-bit/pixel for each RGB color component, four frame buffers with 1024 × 1024 pixels with 8-bit/pixel each, a 64K 24-bit statistical look-up table (LUT), and an 8K 16-bit neighborhood processor LUT. The real-time processor included an arithmetic logic unit (ALU) processing element, a statistical processor, and a neighborhood processor. The image processing board and real-time processor were installed in a Compaq 386/33 microcomputer running the OS/2 version 1.3 operating system and Microsoft C version 6.0 programming language.

Illumination. A cylindrical lighting chamber was internally coated with a flat white enamel paint and was used to provide diffuse reflected light to corn kernels (Casady and Paulsen, 1989). Light was provided by two GE EYC 75W quartz halogen bulbs operated at 10.0 V DC which provided a color temperature of 3200° K. The bulbs were driven by a Brute II 600 regulated DC power supply capable of providing an output voltage deviating by less than ±0.1% from the set point under input voltage conditions that could vary from 105-130 V AC.

View of Objects. With a camera at a fixed position, the machine vision system viewed a limited region of the total surface area of a kernel. For profile measurements, corn kernels were measured alternately with the germ side up or down. Kernels were placed individually on a dark blue background of smooth glass under the camera and were turned over manually. The crown end of the kernel was positioned to be always at the top of the displayed image. The whole corn kernel was segmented from the background and the quality-related regions were isolated from the corn kernel by thresholding specific components of either red, green, and blue (RGB) or hue, saturation, and intensity (HSI) images. From previous experiments, broken regions on corn kernels had the highest optical response with the blue component and the red component usually had a weak response. To obtain a relatively high response of the kernel profile, the green image was used in this research. It is probable that a black and white camera could have been used. Images of the kernel and the isolated quality-related regions were binarized, labeled, and stored in separate regions of interest (ROI) on the same frame buffer of the image board for further analysis.

Kernel Profile Shape Descriptions

Based on domain knowledge of corn kernel shape related to whole or broken kernel status, each corn kernel was divided into three regions, the crown region, the body region, and the tip cap region (fig. 1). The crown region was defined as the region starting at the kernel centroid and located between two 50° angles on each side of the symmetry axis which encloses the crown of the kernel. The tip cap region was the region between two 20° angles on either side of the symmetry axis at the tip cap end. The body region was the region other than the crown and the tip cap regions. From results of the previous and initial experiments, eight morphological features were selected for corn kernel profile shape descriptions. These shape features included two local maximum curvatures along the perimeter, four symmetry ratios along the symmetry axis, one aspect ratio of the kernel, and one tip cap variation ratio of the kernel.

Local Maximum Curvatures. The corn kernel edge was sampled from binarized corn kernel images. The one-dimensional profile signal p(k) was the distance from the centroid of the kernel to a sampling point k on the kernel edge at the angle $\theta_k = \Delta\theta\, k$, $\Delta\theta$ ($\Delta\theta = 2\pi/N$, where N is the total number of sampling points along the kernel edge and N is the power of 2) (fig. 1). The value of N = 128 was used for the entire kernel.

The first edge sampling point was found by searching with the fast line-searching Bresenham algorithm along the direction at $\theta_0 = 0$, which was $\pi/2$ (90°) from the symmetry axis of the kernel image (Hegron, 1988). Then the next edge point was found by searching in the neighborhood of the previously found edge point after

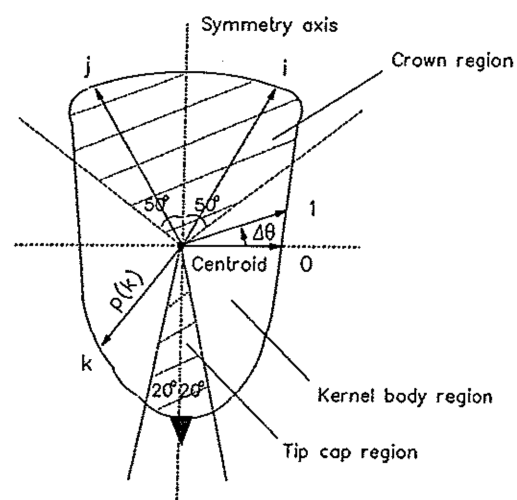

Figure 1–Corn kernel centroid, axes, region locations, and edge sampling points.

moving a counterclockwise angle increment of $\Delta\theta$. The sampling procedure was continued until the whole perimeter was sampled. The curvatures at each sampling point on the kernel perimeter were calculated by the function:

$$|\kappa(k)|^2 = \left[\frac{d^2 p_x(k)}{d\,k^2}\right]^2 + \left[\frac{d^2 p_y(k)}{d\,k^2}\right]^2 \qquad (1)$$

where $\kappa(k)$ is the curvature of profile signal $p(k)$ at the sampling point k; $p_x(k)$ and $p_y(k)$ are the x- and y-coordinate positions of the sampling point k on the kernel edge, respectively, $k = 0, 1, 2, \ldots, N-1$. The local maximum curvatures of the crown and body regions were calculated as the maximum curvatures among the curvatures of all sampling points within their relevant regions. The local maximum curvatures were used for the profile shape discrimination features.

Symmetry Ratio. The symmetry ratio along the major axis was defined as the ratio of the distance from the kernel centroid to the sampling point i to the distance from the kernel centroid to the sampling point j. The sampling point i and j were located on opposite sides of the major axis, respectively, and had the same angle between the major axis. The minimum and maximum symmetry ratios of the crown and of the body regions were used as the four symmetry ratios used as profile shape discrimination features.

Aspect Ratio. The aspect ratio was also used as the kernel profile shape discrimination features. The aspect ratio was defined as the ratio of the length of the major axis to the length of the minor axis which was perpendicular to the major axis.

Tip Cap Variation Ratio. The tip cap variation ratio was defined as the ratio of two distances, $p_{max}(k) = \max\{p(k) \mid k = \text{edge points in tip cap side kernel body region}\}$ and $p_{max}(l) = \max\{p(l) \mid l = \text{edge points in tip cap region}\}$. Distance $p_{max}(k)$ was the maximum distance from the kernel centroid to the sampled tip cap side body region edge points. Distance $p_{max}(l)$ was the maximum distance from the kernel centroid to the sampled tip cap region edge points.

Neural Network Classifier

Neural network classifier is a human neuron structure-like parallel network which performs classification with knowledge stored in the network node connections. The neural network classifier was used for corn kernel profile shape-based breakage inspection and was built from the training results of the backpropagation neural learning algorithm. Backpropagation, also called the generalized delta rule (Rumelhart et al., 1986), is a well-known procedure and has been tested on several large-scale problems (Sejnowski and Rosenberg, 1987; Tesauro and Sejnowski, 1989).

The inputs of the neural network classifier were the eight morphological features and sent to the computer from the image board. To avoid the limitation of a single, hidden layer network (Gibson and Cowan, 1990), the neural network classifier used was a multi-layer, feed-forward network. It had one input layer, one output layer, and two hidden layers. The number of network nodes was selected according to the accuracy and convergence of the training process and optimized during the training. The network had 8 input nodes (8 morphological features), 2 output nodes (whole and broken kernel categories), 32 nodes for the first hidden layer, and 8 nodes for the second hidden layer (fig. 2).

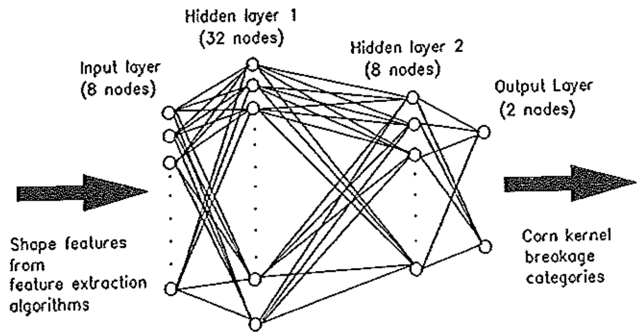

Figure 2–Neural network classifier used for whole/broken corn kernel classification, where the input features are morphological shape description features, and the output is corn kernel breakage category.

The desired neural network was iteratively trained on a set of training exemplars until the tolerance range of the sum of the mean square errors was reached. The neural network classifier was implemented by building a software neural network simulator from the weights of the learned network. The weights were saved in an ASCII file according to the neural network structure by the neural learning algorithm. The input features were normalized using a constant number so that all features stayed within the range of 0.0 to 1.0. The flow chart of the neural learning and corn kernel whole-versus-broken status classification procedure is shown in figure 3.

Training Samples

A training set of 160 corn kernels from the commercial market channel was used. The 160 kernels included 80 whole kernels and 80 broken kernels. The size of a training sample was not necessarily large. The criteria of the training sample selection were:

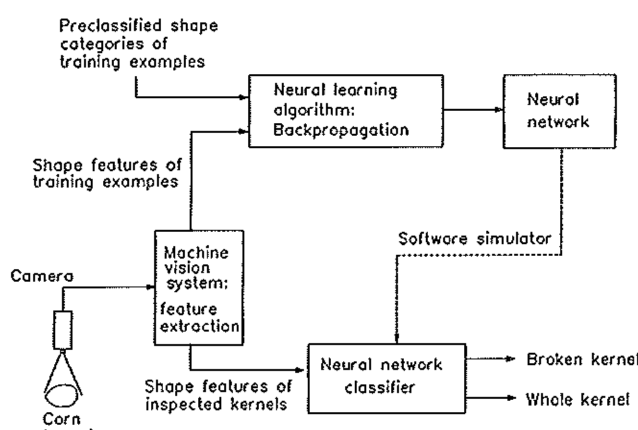

Figure 3–A neural, classifier-based, corn kernel breakage classification system, where the classifier is built by neural learning, and the corn quality is classified by the neural network classifier.

Table 1. Training samples for learning the whole/broken neural classifier

Training Samples	No. of Samples	Description of the Sample Origin and Composition
Whole kernels	80	15 large rounds 15 small rounds 20 long flats 20 short flats 10 small flats with sharply pointed tip cap
Broken kernels	80	50 crown tops broken 20 longitudinal breaks 10 tip cap broken

- The selected sample must strongly represent a particular quality category.
- Every quality category must have at least one sample to represent it.
- Samples weakly representing a particular quality category or unclearly representing more than one quality category were not selected.

The training samples for learning the neural network classifier are shown in table 1.

Test Samples

Samples from six different lots of corn were obtained to evaluate the neural, classifier-based, machine vision corn kernel breakage classification algorithm. The six corn samples were randomly obtained from FR618 × FR600, FR27 × FRMo17, FR1087 × LH123, Commercial 1, Commercial 2, and Commercial 3. The origin and characteristic description of these six samples is given in table 2. For each corn sample, kernels were separated into rounds and flats using a Carter Day Precision Sizer (Carter-Day Co., Minneapolis, MN) with a 4.76-mm (12/64-in.) slotted sieve. The kernels tested were retained by a 6.35-mm (16/64-in.) round-hole sieve and had passed through an 8.73-mm (22/64-in.) round-hole sieve.

Samples of 120 whole and 120 broken kernels (60 round and 60 flat for each breakage category of each corn variety) were randomly chosen from the six corn lots. Each kernel was tested using the neural network whole/broken kernel classifier first with the germ side up and then with the germ side down. The whole kernels were unbroken kernels which had a fully intact profile. The broken kernels included an evenly distributed number of kernels with crowns broken straight across the crown end, angular crown breaks, minor crown breaks, longitudinal kernel breaks, and kernels with tip cap ends broken.

To verify the accuracy of the machine vision system, kernels were classified into whole and broken categories by an experienced human inspector. Then, these kernels were classified by the machine vision system and misclassified kernels were recorded and saved.

Table 2. Corn samples used for the evaluation of the corn kernel breakage inspection algorithm

Corn Variety	Description of the Characteristics of the Test Samples
FR618 × FR600	from agricultural engineering research farm; hand shelled
FR27 × FRMo17	from agricultural engineering research farm; hand shelled
FR1087 × LH123	from agricultural engineering research farm; hand shelled
Commercial 1	unknown varieties from a commercial elevator; combine harvested
Commercial 2	unknown varieties from a commercial elevator; combine harvested
Commercial 3	Keltgen variety from a counter-flow on-farm drying bin; combine harvested

Table 3. Accuracy of whole/broken corn kernel inspection for round kernels with germ side positioned either up or down using a neural network classifier

Classification by Neural Classifier-based Machine Vision System		Human Inspector Classification: Germ Side Up, Whole	Germ Side Up, Broken	Germ Side Down, Whole	Germ Side Down, Broken
FR618 × FR600	whole	53	3	57	2
	broken	7	57	3	58
FR27 × FRMo17	whole	54	4	59	1
	broken	6	56	1	59
FR1087 × LH123	whole	52	4	54	3
	broken	8	56	6	57
Commercial 1	whole	53	4	54	3
	broken	7	56	6	57
Commercial 2	whole	53	4	57	2
	broken	7	56	3	58
Commercial 3	whole	55	3	56	4
	broken	5	57	4	56
Total classification accuracy		89%	94%	94%	96%

Results and Discussion

The results of the machine vision system with neural classifier are summarized in tables 3 and 4. Based on the kernel profile morphological features, the whole/broken kernel neural network classifier had accuracy rates of 89% and 94% for the whole and broken round kernels with the germ side up (table 3), and accuracy rates of 94% and 96% for the whole and broken round kernels with the germ side down (table 3), respectively. Meanwhile, the neural network classifier had accuracy rates of 99% and 96% for the whole and broken flat kernels with the germ side up (table 4), and accuracy rates of 99% and 96% for the whole and broken flat kernels with the germ side down (table 4), respectively. Thus, the flat kernels could be detected more accurately than the round kernels. The flat kernels were

Table 4. Accuracy of whole/broken corn kernel inspection for flat kernels with germ side positioned either up or down using a neural network classifier

Classification by Neural Classifier-based Machine Vision System		Human Inspector Classification: Germ Side Up, Whole	Germ Side Up, Broken	Germ Side Down, Whole	Germ Side Down, Broken
FR618 × FR600	whole	58	2	59	3
	broken	2	58	1	57
FR27 × FRMo17	whole	60	1	59	2
	broken	0	59	1	58
FR1087 × LH123	whole	60	2	60	2
	broken	0	58	0	58
Commercial 1	whole	60	2	60	3
	broken	0	58	0	57
Commercial 2	whole	60	3	60	3
	broken	0	57	0	57
Commercial 3	whole	59	3	59	1
	broken	1	57	1	59
Total classification accuracy		99%	96%	99%	96%

classified with equal accuracy by the neural network classifier with germ side either up or down. Thus, it is likely that the germ did not affect the shape of the binary image obtained for flat kernels.

The false classification of whole kernels into the broken category was caused by a slightly zigzagged edge on the crown end of some flat kernels. The false classification of broken kernels into the whole category was caused by kernels that had part of their tip cap missing and some chips from the crown end missing. Many misclassified broken kernels were very similar in shape to whole round kernels.

The classification accuracy of the neural network classifier for the round kernels was lower than that for the flat kernels; particularly, for round kernels with the germ side up. Besides the same misclassification sources of the flat kernels, the round kernels had their special misclassification source. The round kernels included a certain percentage of irregularly shaped thick kernels, and the profiles of these irregular kernels, particularly with the germ side up, appeared more likely to be broken kernels under the camera lens.

The processing time of the whole/broken corn kernel inspection required about 1.5 s from grabbing the live image to the final classification result. The software-based neural network classifier took about 0.2 s of the 1.5 s and this time would increase with increasing neural network size and structure complexity.

Conclusions

A neural, classifier-based, machine vision system was developed for on-line classification of broken kernels and whole kernels. Based on the corn kernel morphological profile shape features, the neural classifier for whole/broken kernels provided successful classifications of 99% and 96% for whole and broken flat kernels, and of 89% and 94% for whole and broken round kernels, respectively. The flat kernels were very accurately classified for both whole and broken categories with either germ side up or down. The whole round kernels were classified less accurately with germ side up than with the germ side down.

The processing time for the classification required about 1.5 s from grabbing the live image to the final classification result. The software-based neural network classifier required about 0.2 s of the 1.5 s total time. The next step of the research is to combine the breakage classification algorithm with an automated grain kernel feeder mechanism which could theoretically provide operation continuously for 24 h/day.

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